TOWARDS THE GENERATION OF DIGITAL TWINS FOR FACILITY MANAGEMENT BASED ON 3D POINT CLOUDS

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Advances versus adaptation of Industry 4.0 practices in Facility Management (FM) have created usage demand for up-to-date digitized building assets. The use of Building Information Modelling (BIM) for FM in the Operation and Maintenance (O&M) stages of the building lifecycle is intended to bridge the gap between operations and digital data, but lacks the functionality of assessing and forecasting the state of the built environment in real-time. To accommodate this, BIM data needs to be constantly updated with the current state of the built environment. However, generation of as-is BIM data for a digital representation of a building is a labor intensive process. While some software applications offer a degree of automation for the generation of as-is BIM data, they can be impractical to use for routinely updating digital FM documentation. Current approaches for capturing the built environment using remote sensing and photometry-based methods allow for the creation of 3D point clouds that can be used as basis data for a Digital Twin (DT), along with existing BIM and FM documentation. 3D point clouds themselves do not contain any semantics or specific information about the building components they represent physically, but using machine learning methods they can be enhanced with semantics that would allow for reconstruction of as-is BIM and basis DT data. This paper presents current research and development progress of a service-oriented platform for generation of semantically rich 3D point cloud representations of indoor environments. A specific focus is placed on the reconstruction and visualization of the captured state of the built environment for increasing FM stakeholder engagement and facilitating collaboration. The preliminary results of a prototypical web-based application demonstrate the feasibility of such a platform for FM using a service-oriented paradigm.

Key Words: Digital Twins, Building Information Modelling, Facility Management, Point Clouds, Visualization

INTRODUCTION

A Digital Twin (DT) is a digital duplicate of the physical environment, states and processes. While a BIM model contains as-is and historical data, a DT can be used to assess the current state, and to potentially forecast the future state, of a digital duplicate of the built environment (Posada et al. 2015, Grieves 2014). The data used for a DT therefore needs to representative of both the static physical attributes, as well as the dynamic processes and states of the built environment.

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For Facility Management (FM) practices, changes in the built environment that effect the operational status of the work environment need to be recorded and addressed. Current documentation practices for Operation and Maintenance (O&M) procedures within the FM realm include using redundant, often outdated, information that is usually available in paper format only (Teicholz et al. 2013). In order to capture the current physical state of the built environment, 3D point clouds can be used as the basis for as-is BIM and DT representations. The presented research focuses on the design of a primary data acquisition workflow to capture and generate semantically rich data from 3D point clouds, which in turn can be used as basis data for DTs. This allows for routine generation of semantically rich models for enhancing collaboration, decision making, and forecasting amongst FM stakeholders. In the initial design stages of the case study the authors collaborated with FM experts in order to gain insight into the key challenges and requirements. The following key challenges were formed:

1. How can 3D point clouds of indoor environments be routinely acquired without using expensive and specialist hardware?
2. How can large and complex 3D point cloud be processed in order to create semantically rich as-is representations of indoor environments?
3. How can semantically rich 3D point clouds be used to create as-is BIM data?
4. How can service oriented methodologies be used to generate classification results and engaging visualization and analytics outputs to further FM stakeholder engagement?

These challenges are addressed using the described approaches based on state of the art methodology and presented in the case study along with initial results.

RELATED WORK

Generation of digital documentation, used to represent the state of the build environment, relies on as-is BIM data, which can be expensive and time consuming to generate manually (Ochmann et al. 2015). Roper and Payant (2014) state that the benefit of BIM integration for FM practices is allowing centralized access to digital documentation for stakeholders, possibly utilizing the trend of web-based and mobile communications platforms for enhanced communication and data exchange. For example, in indoor environments, BIM integration with FM can visualize spatial attributes to facilitate identification of underutilized spaces, forecast space requirements, simplify space analysis, manage relocation processes, and compare actual with planned space utilization (Becerik-Gerber et al. 2013). The combined use of data sharing principals provides further benefits that enable FM stakeholders from all other related FM practices to have access to critical building operation information (Kensek 2015). Existing buildings often lack as-is BIM documentation due to omitted updating, and unless as-is BIM data is generated, limitations of BIM usage in the O&M phase of existing buildings are expected (Volk et al. 2014). One current method of automated generation of as-is BIM data is with the use of 3D point clouds (Qu and Sun 2015). Dealing with 3D point cloud data comes with specific challenges, as raw point clouds need to be pre-processed before they can be used for generation of as-is digital documentation and reconstructed BIMs, and manual reconstruction is still required to some degree (Macher et al. 2017; Pătrăucean et al. 2015). Most previous research focusing on as-is BIM LOD representations does not include office furniture objects and machinery for indoor environments (Xiong et al. 2013; Tang et al. 2010). Use of BIM and 3D visualization for FM are still at an early stage of adaptation in comparison to other stages in the building lifecycle, though adopter case studies have been described (Kassem et al. 2015; Teicholz et al. 2013). Reconstruction of semantic data for indoor environments, such as offices, poses a particular challenge as reconstructed geometric data is not classified by default, and manual classification is a complex and time consuming process (Chen et al. 2015). Methods based on genetic algorithms and computer vision to verify and optimize the reconstruction of as-is BIM data using 2D images have been proposed as a possible solution to these challenges (Xue et al. 2018). Research by Kalyan et al. (2016) proposed methodology for manual generation of as-is BIM data from 3D point clouds using a Google Tango mobile device. Practicality in terms of user scanning using Google Tango mobile devices, and also low costs and easy setup, has been described by Froehlich et al. (2017). A review of optoelectronic technology developments, applications and benefits for the AEC industry is presented by Pärn and Edwards (2017). Using machine-learning methods, specifically 2D image classification methods known as "multi view classification", the process of generating semantically rich 3D point clouds can be automated, using a trained Convolutional Neural Network (CNN) model to segment and classify point cloud data into as-is BIM representations (Su et al. 2015). In a given scenario this allows FM personnel to upload point cloud scans of office interiors for classification onto a remote server, with the classification or visualization results being streamed back to mobile devices via an online web application (Döllner et al. 2012). The description of a BIM-based multidisciplinary collaboration platform, along with specific technical requirements, has been described in detail by Singh et al. (2010). The visualization-based analytical output of combined as-designed and as-is BIM, point cloud and sensor data can be combined to create a DT that allows for historical and current real-time representations for FM use within the emerging Industry and Real-Estate 4.0 realm (Lasi et al. 2014). Active industry interest for using DTs has been endorsed by large corporations such as SAP (SAP 2018). A key advantage of DTs is centralized access to all information concerning the operational state of a building. This is in contrast to current practices where the owner and the tenant have separate access to the operational state of the building, thus possibly creating a communication barrier for any routine O&M requirements. Additionally, with the unification of data, access privileges can also be controlled better between stakeholders using digital access managements practices (Heidrich et al. 2017).

METHODOLOGY OVERVIEW

The methodology described focuses on O&M stages within the FM operations, particularly on space management. All the research methods outlined in this section, except data fusion (using sensor data), were investigated and utilized in the presented case study. The presented methods were selected based on review, implementation and evaluation of existing methodology outlined in the literature review. Figure 1 illustrates the proposed workflow for incorporating the discussed methods.

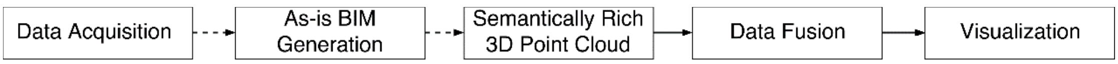

Figure 1: The proposed pipeline for generation of semantically rich 3D point cloud data using a service-oriented approach. The 3D point cloud representation captured in the Data Acquisition stage can be used to optionally create an as-is BIM model in addition to basis data for a DT representation.

A 3D point clouds provides an efficient, affordable, and manageable alternative to capturing the physical state of the built environment (Laing et al. 2015). Scans of varying detail can also be made routinely and can be used to assess physical changes over time. A 3D point cloud consists of what can be defined as non-interpreted data - data that is open to visual interpretation but does not have any semantics associated with it. Unfortunately, point clouds can only be used as "shell representations" of the current physical state built environment. Interior representations, such as Mechanical, Electrical and Plumbing (MEP) components cannot be captured practically using the described point cloud acquisition methods. Thus, point cloud representations by themselves can be thought as LOD-0 representations (or as primary BIM representations). Therefore, 3D point clouds can be used by themselves to represent the current state of the physical environment for practical needs (e.g., assessment of space usage in a room), but for any further representations and assessment the 3D point cloud needs to be processed in order generate useful semantics. These can than be used as the basis for as-is BIMs or DTs (Figure 2). Although there is overlapping between a DT and BIM representations, for this research DTs are treated as a higher-level representation that includes both as-designed and as-is BIM data, and any other associated semantics. A DT representation fuses these as-designed and as-is representations with additional information layers pertaining to the current state of the built environment (such as fusion of sensor data for real-time analysis and forecasting).

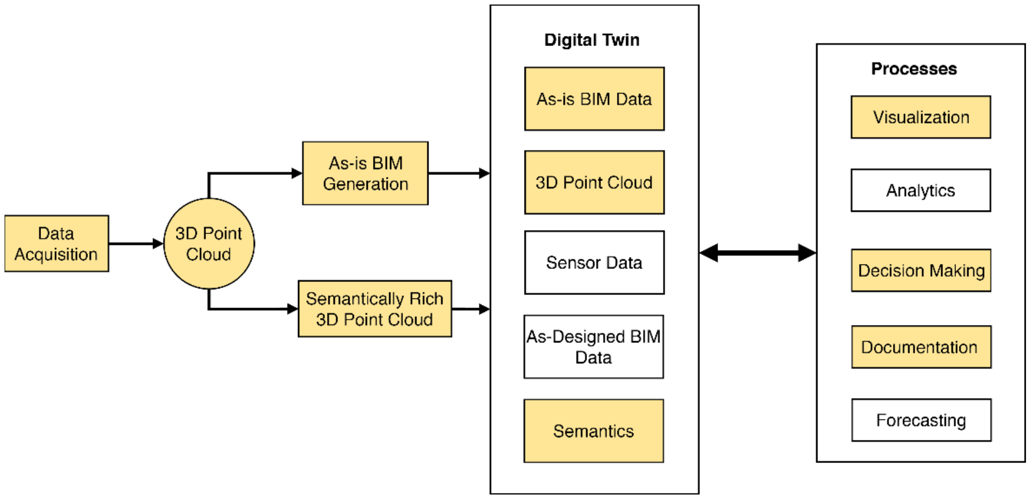

Figure 2: Illustration showing how generation of semantically rich point clouds that can be used as basis data for DTs. The resulting DT can then be integrated with various processes critical to FM using the Industry and Real Estate 4.0 paradigm. The highlighted staged are addressed by the presented case study.

Data Acquisition

With respect to the mentioned points above, the use of mobile phones for capturing and generation of point cloud data has become a viable option (e.g., Google Tango specification compatible consumer mobile devices). The main advantage of using consumer mobile devices with depth sensing cameras is that they provide an affordable, flexible, and simple solution for capturing 3D point clouds of interiors in comparison to more expensive laser scanning devices (Froehlich et al. 2017). The main disadvantage is that the 3D point cloud representations captured using mobile phones may feature lower fidelity in terms of visual details, and contain more noise than using normal 3D scanners for capture. However, very detailed 3D representations of indoor environments are not generally required for routine FM applications. Photometry-based processing methods can be implemented on mobile devices and allow the processing of a sequence of captured images to be converted into a point cloud representation. The visual representation described by a point cloud can be used to enhance FM practices and fulfils the need to be able to have up-to-date representations of interiors of a facility for enhancing and making informed decisions. The process for capturing point clouds is fairly straightforward, and these can be automatically uploaded to a remote server for further processing, documentation, and archiving. In order to acquire 3D point clouds of interiors using a Google Tango compatible device, the user has to actively walk around the given room and focus the device on specific items and areas of interest (Figure 3). The device works by comparing the depth and colour values of sequentially captured image frames. A limitations to this approach is that lighting conditions can affect the quality of the capture (if the interior space is too dark or captured using daytime lighting). Additionally, the user may have to walk around the same area of interest a number of times to generate a complete scan. Once the scan has been generated, the resulting 3D point cloud needs to be filtered for overlapping duplicate points, and preferably sub-sampled to a reasonable degree in order to decrease processing time while preserving the visual fidelity of the 3D point cloud representation.

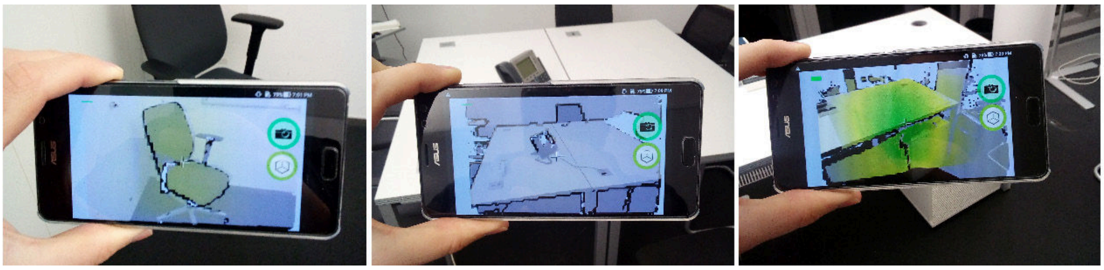

Figure 3: Acquisition of a 3D point cloud of office furniture using a Google Tango compatible mobile phone with the Dot3D app (developed by DotProduct LLC).

As-is BIM Generation

As stated previously, as-is BIMs are not necessarily required for representation of the built environment within a DT, but are required for conformation to BIM practices and more complex representations (such as MEP representations). Captured 3D point cloud data can be used to generate as-is BIM datasets that represent the "core" structural and spatial features of the built environment. The main physical characteristics and major deriving structures can be captured using point cloud to as-is BIM reconstruction. However, as-is BIM reconstruction can generally be thought of as representing global characteristics (e.g., comparison of as-built vs as-designed room layouts), but omits local characteristics such as layout of furniture in an office room for example. Current general research in the Architecture, Engineering, and Construction (AEC) industry is focused on efficient geometry reconstruction at appropriate levels of detail using segmentation and geometry reconstruction methods. One of the key operations for successful reconstruction of as-is BIMs from point clouds is segmentation. Point cloud segmentation is the process of classifying point clouds into multiple homogeneous regions. The segmentation is challenging because of high redundancy, uneven sampling density, and lack of explicit structure of point cloud data (Nguyen 2013).

Semantically Rich 3D Point Clouds

In order to be able to enhance the representation of indoor environments for FM use, an advanced method is required that can automatically approximate the segmentation and semantic labelling of point cloud representations of indoor environments. This can be accomplished using image-based machine learning approaches. Since point cloud scans of indoor environments feature a near-photorealistic representation of the environment, 2D images of 3D point clouds can be used to train and classify images for object recognition tasks (a process known as "multi-view classification", based on Deep Learning image classification principals). An example scenario may include selecting a point cloud cluster of an office containing multiple chairs and tables. To classify this scene using a multi-view classification approach, the scene would be discretized into smaller partitions. At each partition, a number of images would be generated and sent to a server, where the image classification algorithm is running. The algorithm would then return a probability of the classified object contained in that partition, based on the images sent for classification. The classification model would be trained using similar images so it can recognize up to a certain degree of accuracy the object represented by the 2D images of point cloud clusters. This classification label can then be applied to the corresponding 3D point cloud cluster and allow that cluster to be segmented and labelled. This allows for automated segmentation and classification of 3D point cloud clusters of indoor environments. The segmented and labelled point cloud can then be used to generate an as-is BIM representation, or as basis data for a DT representation.

Visualization

The use of interactive 3D visualization can benefit FM stakeholder engagement by allowing real-time display and analysis of 2D and 3D visual outputs generated from the acquired data sources. Using modern computer graphics rendering approaches, complex visualizations can be presented to users in real-time on various configurations including commodity and older hardware. Service-based interactive visualisation can enable streaming of complex visualisation results to thin clients, such as smartphones and tablets. Some mobile devices may be older generation and may not have the ability to process visualisation data in real-time using their native hardware, thus data can be pre-processed and streamed from a server in real-time to the mobile device using an implemented service-oriented architecture solution. Apart from visualization, this approach can also be used for complex computation such as the image-based point cloud classification approach that is outlined in this paper. Figure 4 shows a high-level flowchart to illustrate this concept. Real-time sensor data can also be overlaid over the semantically rich point cloud representation to allow for a generalized representation. This allows for point cloud attributes such as shape and colour to be changed over time. This approach can be used for visualization of recorded changes in the built environment in real-time (Khan and Hornbæk 2011).

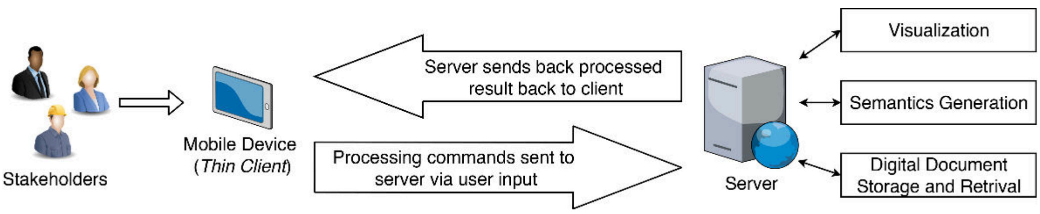

Figure 4: High-level overview for a service-oriented approach for 3D visualization of BIM data.

CASE STUDY

The case study addresses the presented challenges outlined in the introduction section and provides an overview of the approaches for the implementations of the Visualization, Decision Making and Documentation processes (Figure 2). The following possible solutions to the challenges were derived from the case study:

1. The adopted methodology is focused on using mobile phones for capturing 3D point clouds. Using Google Tango compatible mobile devices allows for routine capture and generation of point cloud representations of interior spaces (e.g., office spaces, conference room, and storage spaces).
2. Once 3D point clouds have been captured, using segmentation algorithms the 3D point clouds can be processed to extract and classify features such as walls, floors, and ceilings. For more complex items such as chairs and desks, multi-view classification is used. This allows for the generation of semantically rich point cloud representations of interior spaces.
3. Semantically rich point cloud data can then be processed and converted to IFC data representative at BIM LOD-300 or used as basis data for a DT representation. For the case study, we have used two different point cloud data sets (one of an empty hallway and another of an office interior with furniture objects).
4. The classification and visualization of semantically rich point cloud was implemented using a service-oriented approach as a web-based prototype application.

RESULTS

Generation of as-is BIM Data

For first part of the case study, a result from an as-is BIM reconstruction of a point cloud scan of an office hallway to the IFC format at LOD-300 is presented. Using a combination of automated segmentation of planar surfaces (walls, floors, and ceilings), and manual selection, bounding areas of segmented clusters were labelled and converted to IFC representational hierarchy components manually (Figure 5). The interior of the office hallway was scanned using commercial indoor laser scanner (this scan was provided as test data by FM stakeholders). Removal of scanning artefacts (e.g. noise and other outlier point data), was accomplished manually, though can be automated as well with varying degrees of success. The segmentation of a point cloud of this size (1 053 735 points) takes a few minutes using a modern GPU-based processing pipeline (Richter et al. 2015). For verification of reconstructed geometry, deviation analysis methods previously investigated by the authors can be used (Stojanovic et al. 2017).

Generation of Semantically Rich 3D Point Cloud Interior Representations

For the second part of the case study, a prototype web-based application was implemented that is able to process and analyse given 3D point clouds of typical indoor office spaces and create corresponding up-to-date approximations of classified segments and object-based 3D models. The presented 3D point cloud of an office interior with furniture was first manually segmented to detect walls, floors and ceilings, and then using machine learning the furniture objects were detected and classified. To enable clear, efficient, and direct stakeholder engagement, a platform for collaborative generation and review of as-is representations and associated digital documentation is required. The approach is based on the author's previous research (Stojanovic et al. 2018). The results in Figure 6 show that the multi-view classification system (based on machine learning) is able to provide a sufficient description of the composition of objects in the scene. The multi-view classification approach is used for fast labelling and extraction approximations of indoor spaces. In the test case a scan of an office was created (featuring 27 331 points). This 3D point cloud scan was captured in a few minutes using a Google Tango compatible mobile device (Asus

ZenFone AR). This scan was then uploaded for classification via a custom web-based application to a server running the classification model. In terms of performance, a scene with approximately 30 000 points can be classified within two minutes average using a commodity PC with a modern CPU and GPU. Additionally, the reconstruction of classified point clouds is possible by placement of 3D furniture models. This allows for a better visual approximation of the spatial arrangement of furniture objects.

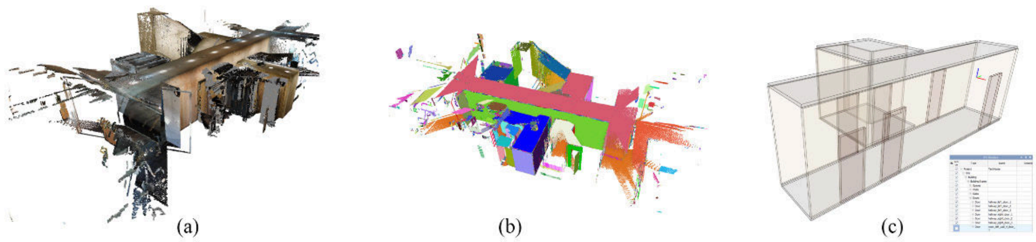

Figure 5: (a) Shows the original point cloud, while (b) shows the segmented point cloud that includes different coloured planes to denote different point cluster orientations in comparison to other cluster regions in the point cloud data set. (c) Shows the initial results of segmentation and reconstruction of an office hallway from a 3D point cloud at LOD-300.

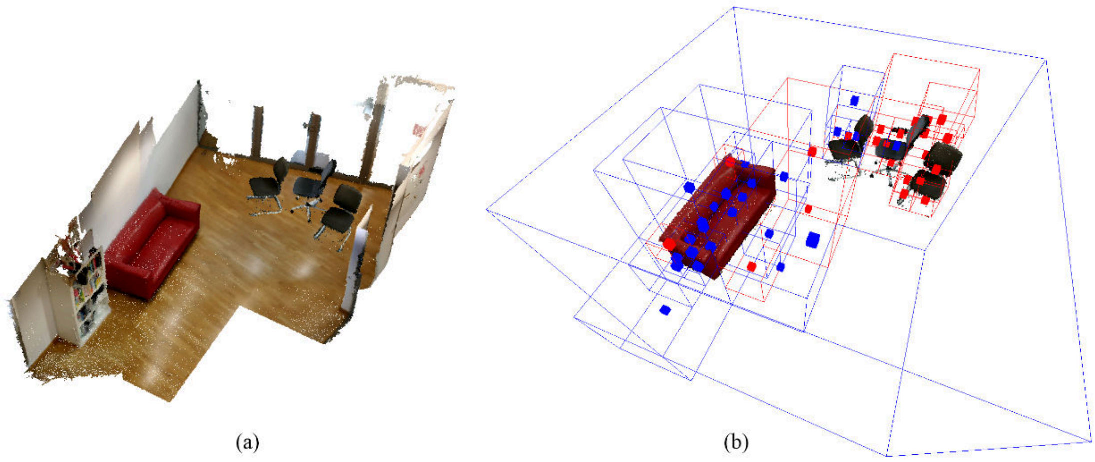

Figure 6: Classification results of an indoor office area containing a sofa and chairs. (a) Shows the input point cloud and the segmented region that is to be classified, and (b) shows the classification output. In the classification output, the blue cubes indicate possible spatial location of a sofa and the red cubes indicate possible spatial positions for chairs.

CONCLUSIONS AND FUTURE WORK

The results have demonstrated the feasibility of generating as-is data representations of indoor environments with commodity hardware for FM use (specifically space management). The described approach has potential to increase engagement and enhance decision making for FM practitioners who are currently adopting BIM practices. Using a service-oriented paradigm, the scanned indoor environments obtained using consumer mobile devices can be reconstructed as semantically rich as-is BIM data, and as basis data for DTs. The described methodology provides a detailed overview of the processes required for acquiring, generating, and presenting this semantically rich as-is data. There are limitations of the described methods and approaches. First, for the generation of as-is BIM data from point clouds, the selection and labelling of segmented areas to be converted to IFC components still required manual user input. Second, for the generation of semantically rich point clouds using multi-view classification, additional user annotation and correction is required after the classification stage for most cases. To address this, the development of a web-application for centralized access to 3D point clouds and capability for visualizing sensor data is ongoing. With this web-based application, multiple users can collaboratively review, annotate, and comment on the segmented and annotated as-is point cloud representations of interior environments. The third limitation is routinely captured 3D point clouds can require increased computer storage space and computer networking, thus appropriate IT infrastructure is required. Further investigation of incorporating sensor data analytics for the "data fusion" stage is also planned. A pilot study with FM practitioners using the described methodology workflow is planned for later stages of this research.

REFERENCES

Becerik-Gerber, B., Jazizadeh, F., Li, N., & Calis, G. (2011). Application areas and data requirements for BIM-enabled facilities management. Journal of construction engineering and management, 138(3), 431-442.

Chen, K., Lai, Y. K., & Hu, S. M. (2015). 3D indoor scene modeling from RGB-D data: a survey. Computational Visual Media, 1(4), 267-278.

Döllner, J., Hagedorn, B., & Klimke, J. (2012). Server-based rendering of large 3D scenes for mobile devices using G-buffer cube maps. In Proceedings of the 17th Int. Conf. on 3D Web Technology (pp. 97-100). ACM.

Froehlich, M., Azhar, S., & Vanture, M. (2017). An Investigation of Google Tango® Tablet for Low Cost 3D Scanning. In ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction (Vol. 34). Vilnius Gediminas Technical University, Department of Construction Economics & Property.

Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. White paper. Retrieved April 03, 2018, from https://tinyurl.com/y9wrpj43

Heidrich, J., Becker, M., Kuhn, T., Kleinberger, T., Damm, M., & Duell, A. (2017). Systems Engineering as an Enabler for Future Innovation. Tag des Systems Engineering: Paderborn, 8.-10. 87.

Kalyan, T. S., Zadeh, P. A., Staub-French, S., & Froese, T. M. (2016). Construction quality assessment using 3D as-built models generated with Project Tango. Procedia Engineering, 145, 1416-1423.

Kassem, M., Kelly, G., Dawood, N., Serginson, M., & Lockley, S. (2015). BIM in facilities management applications: a case study of a large university complex. Built Environment Project and Asset Management, 5(3), 261-277.

Kensek, K. (2015). BIM guidelines inform facilities management databases: a case study over time. Buildings, 5(3), 899-916.

Khan, A., & Hornbæk, K. (2011). Big data from the built environment. In Proceedings of the 2nd international workshop on Research in the large (pp. 29-32). ACM.

Laing, R., Leon, M., Isaacs, J., & Georgiev, D. (2015). Scan to BIM: the development of a clear workflow for the incorporation of point clouds within a BIM environment. WIT Transactions on The Built Environment, 149, 279-289.

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239-242.

Macher, H., Landes, T., & Grussenmeyer, P. (2017). From Point Clouds to Building Information Models: 3D Semi-Automatic Reconstruction of Indoors of Existing Buildings. Applied Sciences, 7(10), 1030.

Nguyen, A., & Le, B. (2013). 3D point cloud segmentation: A survey. In Robotics, Automation and Mechatronics (RAM), 2013 6th IEEE Conference on (pp. 225-230). IEEE.

Ochmann, S., Vock, R., Wessel, R., & Klein, R. (2016). Automatic reconstruction of parametric building models from indoor point clouds. Computers & Graphics, 54, 94-103.

Pärn, E. A., & Edwards, D. (2017). Vision and advocacy of optoelectronic technology developments in the AECO sector. Built Environment Project and Asset Management, 7(3), 330-348.

Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., de Amicis, R., ... & Vallarino, I. (2015). Visual computing as a key enabling technology for industrie 4.0 and industrial internet. IEEE computer graphics and applications, 35(2), 26-40.

Qu, T., & Sun, W. (2015). Usage of 3D Point Cloud Data in BIM (Building Information Modelling): Current Applications and Challenges. Journal of Civil Engineering and Architecture, 9(11), 1269-1278.

Richter, R., Discher, S., & Döllner, J. (2015). Out-of-core visualization of classified 3d point clouds. In 3D Geoinformation Science (pp. 227-242). Springer, Cham.

Roper, K. O., & Payant, R. P. (2014). The facility management handbook. AMACOM Div American Mgmt Assn.

SAP (2018). Leonardo Innovation Services Showroom. Retrieved April 03, 2018, from https://discover.sap.com/innovation-showroom-demo/en-us/digital-twin.html

Singh, V., Gu, N., & Wang, X. (2011). A theoretical framework of a BIM-based multi-disciplinary collaboration platform. Automation in construction, 20(2), 134-144.

Stojanovic, V., Richter, R., Döllner, J., & Trapp, M. (2017). Comparative Visualization Of BIM Geometry And Corresponding Point Clouds. International Journal of Sustainable Development and Planning, 13(1), 12-23.

Stojanovic, V., Trapp, M., Richter, R., & Döllner, J. (2018). A Service-Oriented Approach for Classifying 3D Points Clouds by Example of Office Furniture Classification. In Web3D '18: The 23rd International Conference on Web3D Technology. ACM.

Su, H., Maji, S., Kalogerakis, E., & Learned-Miller, E. (2015). Multi-view convolutional neural networks for 3d shape recognition. In Proceedings of the IEEE international conference on computer vision (pp. 945-953).

Tang, P., Huber, D., Akinci, B., Lipman, R., & Lytle, A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Automation in construction, 19(7), 829-843.

Teicholz, P. (Ed.). (2013). BIM for facility managers. John Wiley & Sons.

Volk, R., Stengel, J., & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings—Literature review and future needs. Automation in construction, 38, 109-127.

Xiong, X., Adan, A., Akinci, B., & Huber, D. (2013). Automatic creation of semantically rich 3D building models from laser scanner data. Automation in Construction, 31, 325-337.

Xue, F., Lu, W. and Chen, K. (2018), Automatic Generation of Semantically Rich As-Built Building Information Models Using 2D Images: A Derivative-Free Optimization Approach. Computer-Aided Civil and Infrastructure Engineering. doi:10.1111/mice.12378